Using Twitter to Predict Investor Decisions

Honors Thesis

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Abstract

Since the stock market's inception in the 17th century, people's thoughts and feelings have played a part in a stock's success in trading. Obviously, company performance and an investor's rigorous analysis of a stock drive most valuation, but it has been demonstrated that, especially in the short term, investors' cognitive biases drive some decisions as well. What if an investor knew how others felt about a company? What if they could see a facet of those biases? With this kind of information, investors and companies could make more informed and profitable decisions every day. With technology today, we may have a tool that shows how people feel in regards to a company: Twitter. I ask the question: can Twitter be used to predict how an individual stock will move on a given day? Using DiscoverText, an application that collects Tweets based on keywords, I collected data on Tweets about three major corporations: Home Depot, Starbucks, and Southwest Airlines. WordStat, an application that counts words in text data, was used to code positive and negative sentiment for Tweets. SPSS was then used to develop a Time Series regression model. Results indicate predictive relationships between the stock price of a company and positive Tweets, negative Tweets, and the number of words in each Tweet. The study finds a statistically significant relationship between the sentiments, volume of Tweets, and stock price, but the relationship differs between companies. Future research needs to determine if this is because of difference in product or some other factor. Going forward, my research has the ability to play a role in larger models and allow investors to make more educated and more profitable investing decisions.

Acknowledgments

I would like to express my gratitude to my advisor, Dr. Dan McDonald. At times during this research, I found myself overwhelmed and a bit lost. Dan really grounded me and gave me focus. We spent countless hours in his office working through data and models and I never would have gotten here without him. He never hesitated in trying to make time in his schedule for us to work together. He always worked with a smile and showed incredible patience explaining statistical concepts to me that I had no experience with. I would also like to thank Dr. Patricia West. She always made herself available to me and shaped my thoughts on how to accurately look at the data. She also helped organize my thoughts when I found myself getting confused. Additionally, I never would have gotten to this point without Ralph Greco. Time spent in his Business Analytics class changed how I think about and look at data. I believe that throughout the rest of my life, some of the lessons I learned in his class will go forward with me. Finally, I would like to thank my parents, my siblings, and my day one friend Austin for all the positive support throughout my entire life in bringing me to where I am today.

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Chapter 1: Background & Prior Research

The Stock Market: A term known to many, but well understood by few. The term now reminds many of modern images such as those during the Financial Crisis of 2008, but what could be called the "modern stock exchange" has actually been around since 17th century Amsterdam, when the Dutch East India Trading Company first formed and distributed shares of ownership in their company, or "stock." What made this a modern exchange is the development of a secondary market and the rapid exchange of shares on that market (Petram). Now, nearly 400 years later, we have dozens of exchanges on which thousands of companies are traded every day.

The primary market is when stocks are first sold from the selling company to institutional investors. It is then that institutional investors begin to sell these shares on the secondary market, which anyone with the necessary resources to purchase a stock can access. My research concerns the trading of stocks on the secondary market and not the primary market. The purpose of investing in the secondary market is to make money. Outside of receiving dividends, money paid out to shareholders of a company, one makes money on the market by buying a security at a low price and selling it at a high price. But how is one to know when a stock is at a high price or a low price? One must know its value.

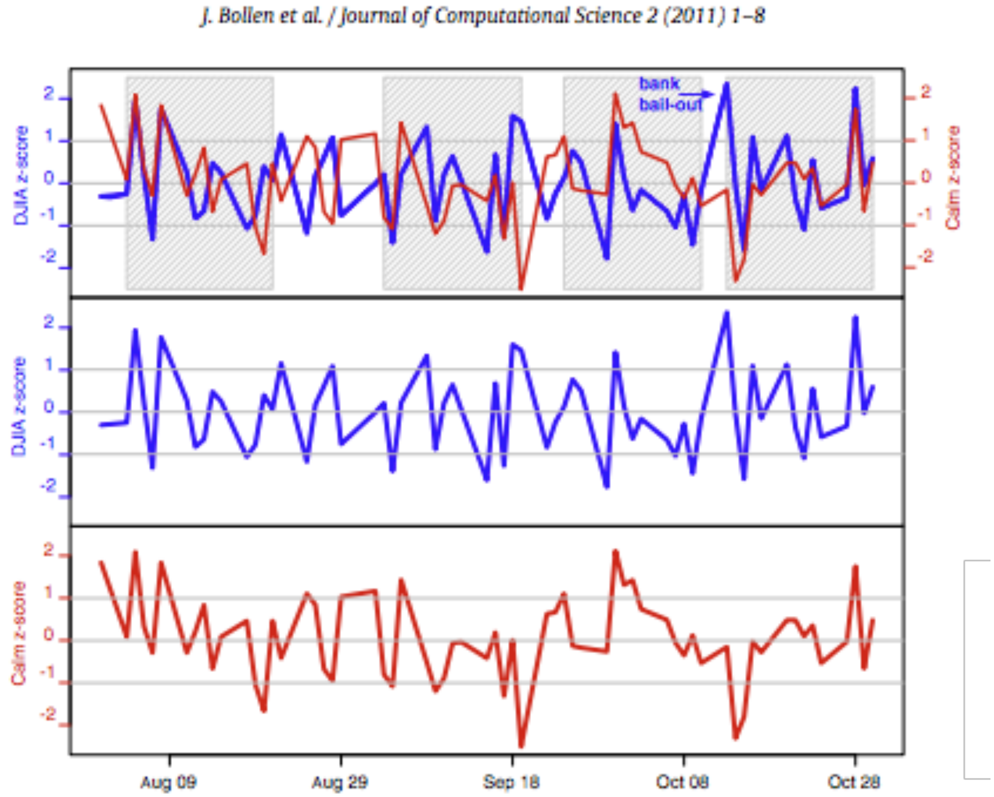
The best way to value a stock will continue to spark debate as long as the stock market exists. Classic finance teaches different methods such as the Dividend Discount Model, Gordon Growth Model, and Present Value of Operating Free Cash Flows. All of these, and all the other fundamental stock valuation models, value companies based on their cash flows, growth opportunities, assets, sales, or some combination of these and other factors in order to find a fair price for a company. Based on these analyses, an investor might purchase or sell a stock if they think it is under or overvalued. On the other hand, behavioral finance argues that this market does not act so rationally. Behavioral finance says that investors often act upon biases and that, “Evidence of these biases has typically come from cognitive psychology literature and has then been applied in a financial context” (Byrne 1). Byrne speaks to past research talking about how investor sentiment, over & under reaction to new information, and other cognitive biases have been proven to affect investor decisions based on empirical evidence.

In other research, John Nofsinger looks at the connection between mood and stock market movement (investing decisions). He walks through the decision of an average investor, using portfolio and investing theories to make trades. Nofsinger cites other research, an example being Au et al. where Nofsinger says, “They find that traders in a good mood environment tended to be overconfident, take unwarranted risks, make less accurate decisions, and perform poorly” (148). Au et al. found the opposite of bad mood environments. Through Nofsinger’s research, he concludes that, “The general optimistic/pessimistic mood of society is transmitted through social interaction, and in turn influences all types of decision-makers, including financial ones” (157). Investor decisions are clearly influenced by factors outside of unbiased analysis. Because this has been proven to be true, it would be infinitely valuable to know the world’s thoughts and feelings on a stock to give some indication on the direction the stock will move.

In today's world of social media, we do have some indication as to what individuals are thinking on a daily basis. Twitter may be the most widely used indication of the aggregate thoughts of the world throughout the day. Twitter is an application developed in 2006 that allows individuals to share their thoughts and ideas in 140 characters or less. Twitter, now a company as well as an application, has grown to 320 million monthly active users (Twitter). All these millions of Tweets put together may give some indication to trends across the world and more specifically, the macro economy. Prior research has given some validity to this notion.

John Bollen et al. examines this idea in "Twitter Mood Predicts the Stock Market." They cite recent research that suggests that early indicators of various economic and commercial events can be found in social media. They then seek to find if this connection would also be true for social media, specifically Twitter, and the stock market. Bollen et al. were successful in finding a connection in one experiment. They used tweets from February-December 2012 and only used tweets with explicit statements of mood (approximately 10 million tweets). Google Profile of Mood States measures mood in terms of six dimensions: Calm, Alert, Sure, Vital, Kind, and Happy. One of these dimensions, the measure of the "Calmness" in the public tweets, correlated strongly ($p=.009$) in a linear pattern with the Dow Jones in a three-day lag. It should also be noted that this is measuring Z score, so it is measuring overall deviation in a Granger causality analysis and they don't necessarily move in the same direction, but with the same strength of deviation. The trends can be seen in in the figure below.

Figure 1: Calmness Deviation Compared to Stock Market Deviation



The researchers then did a non-linear Self Organizing Fuzzy Neural Network (SOFNN) model using the Dow Jones compared with various combinations of the 6 mood dimensions. The strongest predictor was the Calm and Happy dimension combined together to predict the up and down movement of the index in a binomial system. The 87.6% accuracy over the trials had a 0.32% chance of occurring out of complete chance. In conclusion, in both the linear and non-linear trials some aspect of public mood showed predictive ability of the Dow Jones Industrial Average in a lag of three days.

Another study, "Predicting Stock Market Indicators Through Twitter: I hope it is not as bad as I fear," came to a similar conclusion as the previous study. Their method consisted of analyzing approximately 30,000 tweets per day over a year long period that had "mood words" in them: hope, happy, fear, worry, nervous, anxious, and upset. Zhang et al. then looked at the mood word occurrences with a three day lag compared to stock indices, which matches up quite well with Bollen's research. As you can see in the figure on the next page, hope in a three-day lag and hope combined with fear and worry in a three-day lag both correlated very strongly and negatively with the three stock indices. As emotions spike, the indices drop. These emotions deal with uncertainty, so when they are high, markets do not perform well. The measures correlated strongly and positively with VIX, which measures the volatility of the market. This makes sense because as emotions spiked, so did volatility. As Zheng says, "To put it in simple words, when the emotions on twitter fly high, that is when people express a lot of hope, fear, and worry, the Dow goes down." (61).

Figure 2: Hope, Fear, and Worry Measures Compared to Stock Indices

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	Dow	NASDAQ	S&P 500	VIX
Hope%	– 0.381**	– 0.407**	– 0.373**	0.337*
Hope%-2 mean	– 0.618**	– 0.631**	– 0.607**	0.518**
Hope%-3-mean	– 0.737**	– 0.738**	– 0.724**	0.621**
Fear%	– 0.208 *	– 0.238 *	– 0.2	0.235*
Fear%-2-mean	– 0.259*	– 0.285**	– 0.253*	0.312**
Fear%-3-mean	– 0.346**	– 0.368**	– 0.342**	0.403**
Worry%	– 0.3**	– 0.305**	– 0.295**	0.305*
Worry%-2-mean	– 0.421**	– 0.415**	– 0.414**	0.410**
Worry%-3-mean	– 0.472**	– 0.460**	– 0.467**	0.459**
Hope+Fear+Worry%	– 0.379**	– 0.405**	– 0.37**	0.347*
Hope+Fear+Worry%-2-mean	– 0.612**	– 0.625**	– 0.6**	0.532**
Hope+Fear+Worry%-3-mean	– 0.726**	– 0.728**	– 0.713**	0.633**

Table 6. Correlation Coefficient of average emotional tweets percentage and stock market indicators (N=93)
**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

All this research into the topic of Twitter and the stock market led me to the question of whether this thinking could be applied to individual companies. Could using Tweets help one to predict how an individual stock will move, or have any kind of relationship at all? Through the rest of this paper, I will describe the testing of the following hypothesis:

1) The volume of Tweets about a company (the amount the company is being talked about) or the feelings people express toward a company over Twitter will show a relationship with the company's stock performance.

Chapter 2: Methods

The hypothesis will be tested by analyzing different datasets consisting of Tweets from three companies: Home Depot, Starbucks, and Southwest Airlines. Each dataset contains 50,000 Tweets. The Home Depot dataset covers a span of 35 days (November 30th-January 6th). The Starbucks dataset covers a span of 24 days (December 7th-December 30th). The Southwest Airlines dataset covers a span of 46 days (December 7th-January 21st). I chose these companies because they all have active Twitter accounts and they are brands that consumers often interact with on Twitter.

Data Collection

I used an application called DiscoverText to collect Tweets. The application can collect Tweets based on a number of commands. I used keywords to flag the Tweets and relied on DiscoverText coding to accurately do so. For example, I had the application grab Tweets with the phrase "Home Depot." This eliminated any misleading data that only contained the word "home" or only the word "depot." This also worked well for Starbucks. For Southwest Airlines, I ran into some issues realizing that a lot of people will reference the company simply by saying "Southwest," but using that keyword would gather a lot of Tweets not related to the airline. I decided to use it as a keyword regardless. Upon collection of all the Tweets, a 50,000 Tweet random sample was taken from each, as this was the limit for a random sample to export from DiscoverText.

I later used another application called Wordstat to sort through the Southwest data. When words associated with flying were in the Tweet, they were definitely kept.

When some other top used words that Wordstat summed (such as the College Football Bowl Game with "Southwest" in the title) that had nothing to do with the airline, the Tweets were removed. There were undoubtedly some Tweets unrelated to Southwest that were overlooked and kept in the dataset, but when aggregated won't make a substantial difference.

From Yahoo! Finance, I downloaded the open/close stock price on each day there was data for each company and the S&P 500. In some tests of the hypothesis, the S&P 500 is controlled for as the direction of the index is naturally correlated with the direction of individual stocks. In some tests, I wanted to find the unexplained variance that the S&P did not predict to see if Twitter data could. The S&P 500 was used instead of the Dow Jones (as some of the prior research had done) because the S&P 500 essentially contains the 500 largest companies trading publicly while the Dow Jones only contains 30 companies. The S&P should predict the movement of individual stocks better.

Variables & Model Choice

Upon extracting the Twitter data from DiscoverText, I needed to aggregate it in order to create the necessary independent variables. I used SPSS to get both the sum and mean of the number of Tweets on each day and number of total words. Additionally, I uploaded a positive/negative/neutral dictionary add-on to WordStat. Using that, WordStat was able to characterize all the words in each dataset as positive, negative or neutral. I then found the sum and mean of all these types of words on each day to get the following categories: negations, negative, not bad, not good, positive, real bad, and real good. To clarify, “not good” would occur in a Tweet such as, “The Starbucks coffee was not pleasing today.” So, a word like pleasing in this case would not be categorized as a positive word. This left a total of 18 independent variables from the Twitter data. Additionally, the S&P 500 open and close prices were used as independent variables.

The open and close prices of the individual companies were used as the dependent variables. For each dataset of company prices, I wanted to find which of the independent Twitter variables indicated a relationship with the dependent stock price variables, whether it was the opening or closing price. Based on prior research, I assumed that I would need to do a cross correlation and examine the relationship between the variables on a number of different lags. Hopefully, I would find that the Twitter data preceded the stock price and not the other way around. Once I found which Twitter factors proved a relationship with stock price, I used them to make three ARIMA (autoregressive integrated moving average) models, forecasting stock price while controlling for the S&P 500. I am using an ARIMA model to remove the trend that is characteristic of any kind of time series model. The series was detrended, so that the daily values can be predicted. In a time series model the best predictor of what happens today is what happened in the past (yesterday or a few days before). An ARIMA model also takes non-stationary data and tries to make it stationary, meaning that certain statistical properties, such as the variance, do not change extensively over time.

Data Transformation

Some transformation of the data had to take place because of the nature of stock price data. Twitter is active every day of the week, while the stock exchanges are closed on the weekend. So, there were two days of Twitter data with no corresponding stock price data. There were a few different ways to approach this problem, each of which I would try. For one, I could just ignore the weekend Twitter data. The issue here is that if Twitter predicts stock price over a lag of a few days, it might not be accurate because for example, instead of Sunday Twitter data predicting Monday stock price, we would see Friday Tweets matched with Monday stock price which could be too long of a lag and miss crucial data. Secondly, I could ignore Friday and Saturday Twitter data. This would allow for Sunday data to be predictive of any of the stock prices in the rest of the week. Thirdly, I could ignore Thursday and Friday Twitter data so that Saturday and Sunday Twitter data could be used to forecast the stock price during the week. Each method had the potential to lose critical predictive data so I had to be sure to try each one.

Chapter 3: Results

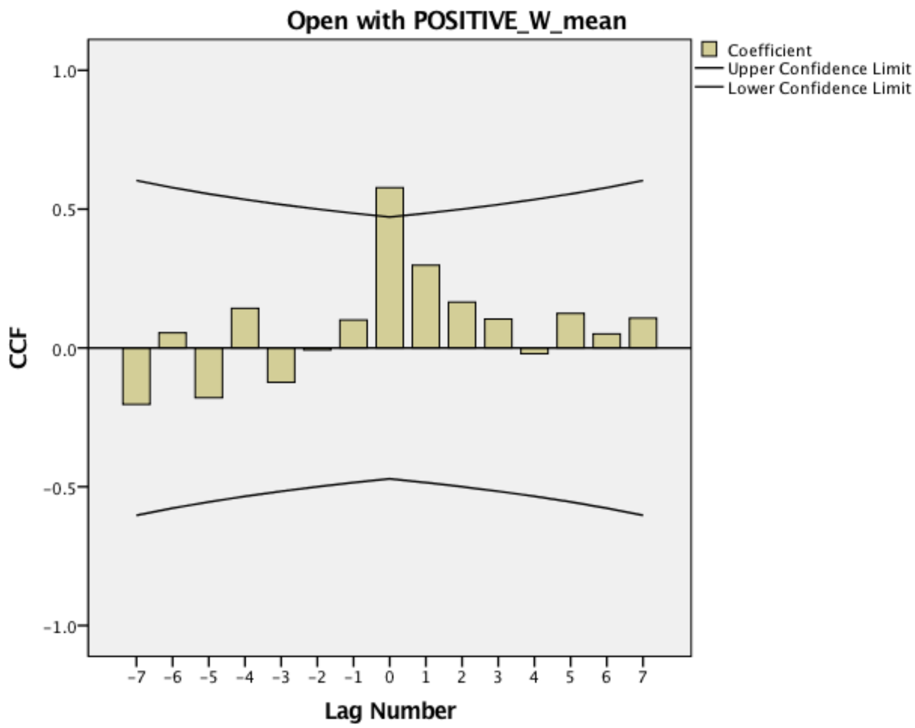
Cross Correlation

For each data set, I created three additional data sets (a total of 12). The three additional sets matched stock price with Tweets from 1 day before, 2 days before, and 3 days before, as described above. I had to do it this way because the ARIMA models could not read the Twitter data matched with empty corresponding stock prices (the weekend). In each of the 12 datasets, I had to delete unused days of Twitter data, so each set had different Twitter data matched to each day stocks were traded.

For all three companies (Home Depot, Starbucks, and Southwest) I found that the dataset using Sunday (a one-day lag) was the most effective. The dataset with no lag, a 2-day lag, and a 3-day lag were not as significant or not significant at all. So, throughout the rest of the results, I will be referring to the dataset containing stock prices for Monday-Friday, but matched with Twitter data from Sunday-Thursday in a one-day lag.

For each of the three one-day lag company datasets I performed an ARIMA analysis, but first provide information related to the cross correlations. The dependent variables were the open and close price of each company. I tested all the independent variables mentioned above (except S&P 500 price for now) to see which showed a relationship with stock price. Below, you can see some examples of where there was a significant relationship for Starbucks. In the cross correlation, a lag value of “0” really means a lag of one as I manually lagged the dataset before inputting into this model.

Figure 3: Starbucks Open Price with the Mean of Positive Words



In Figure 3, the mean of positive words found in Starbucks tweets on each day showed a significant positive correlation in a lag of 1 (shown by moving above the upper confidence limit) with the open price of Starbucks. In Figure 4, there is interestingly a negative significant relationship between the sum of positive words in all Tweets on a given day and the open stock price of Starbucks on the following day. Figure 5 follows the trend of Figure 4, showing a negative significant relationship between the sum of all the words in all the Tweets on a given day and where the next day's closing price is. You can view Figures 6-8 those relationships. For the most part across all companies, it did not matter whether the open or close was used. If there was a correlation for the sum of total words with open, then most often there was a correlation with close as well.

Figure 4: Starbucks Open Price with Sum of Positive Words

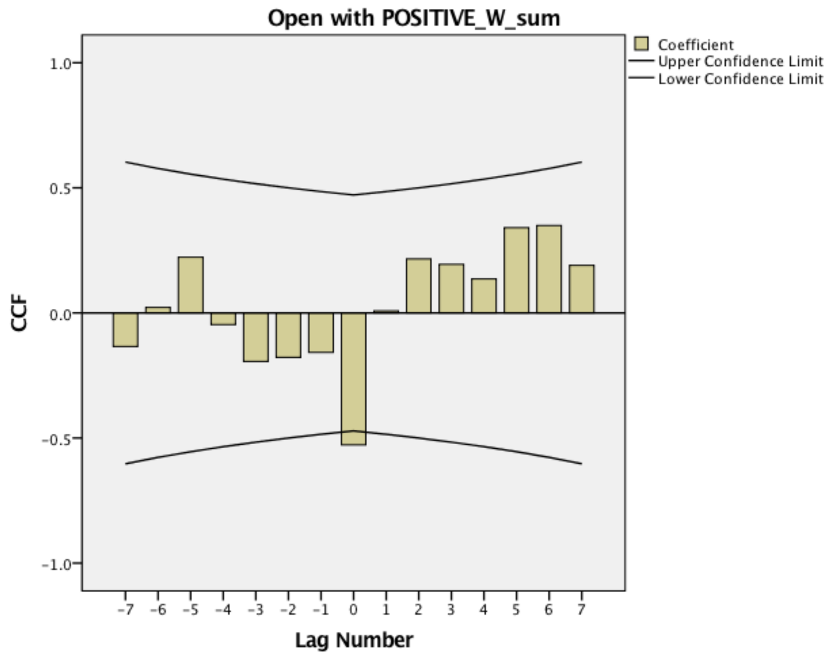


Figure 5: Starbucks Close Price with the Sum of Total Words

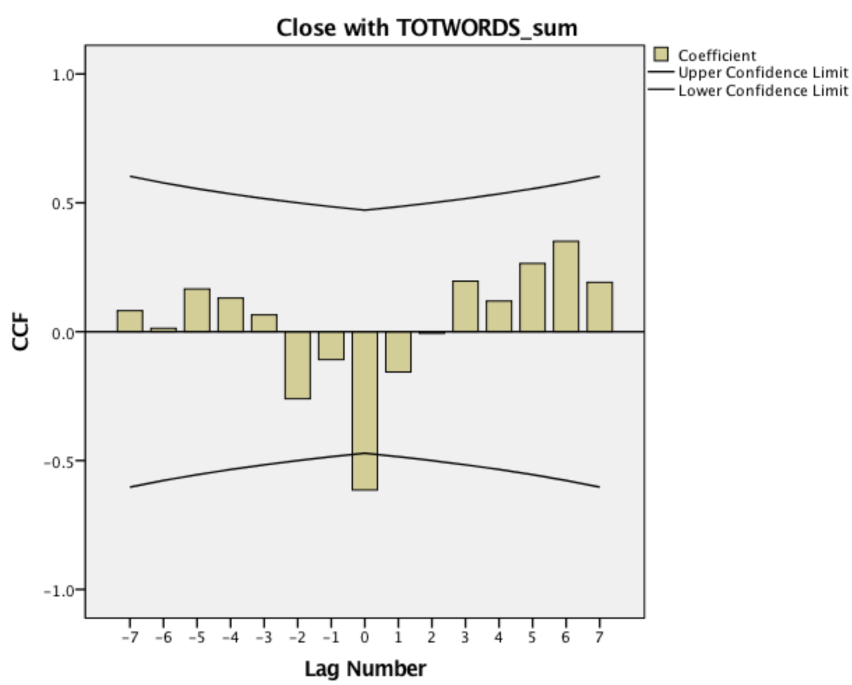


Figure 6: Starbucks Close Price with Sum of Negative Words

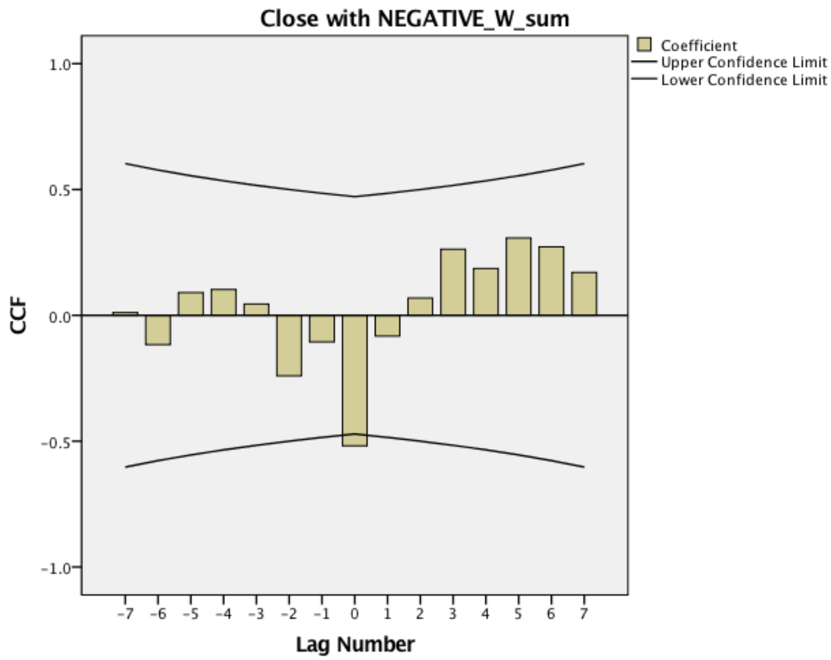


Figure 7: Starbucks Close Price with Sum of Positive Words

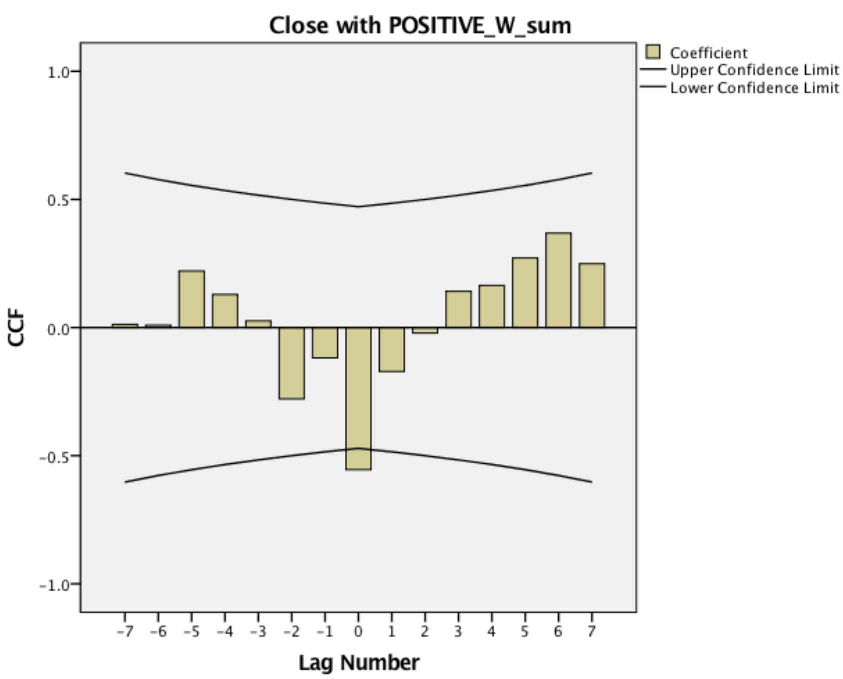
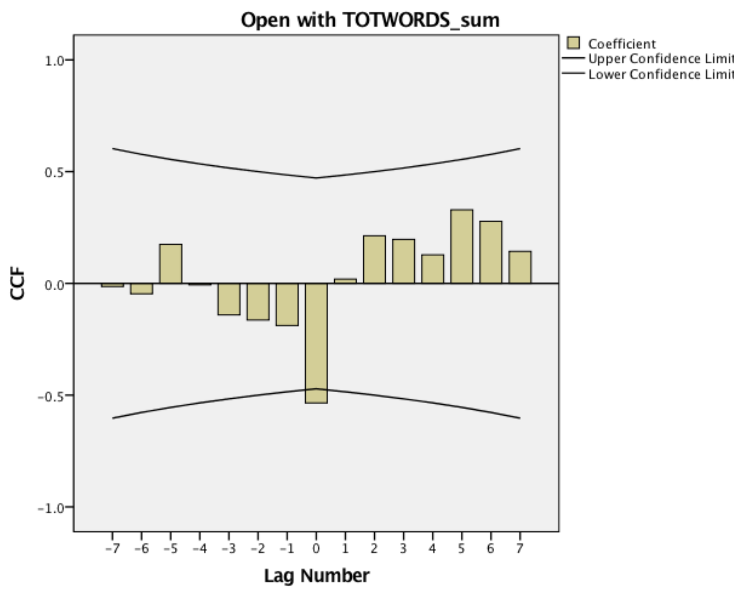


Figure 8: Starbucks Open Price with Sum of Total Words



Moving on in the analysis, I only use open price as the dependent variable to make things more consistent. These tables are only examples of what the Starbucks data showed, but I found similar results for Home Depot and Southwest in a one-day lag. For Home Depot, the sum of total words had a negative correlation with the open and the mean of negative words had a positive correlation with the open. For Southwest, the mean of negative words and the open price had a positive correlation. In no test did the mean or sum of total number of tweets, negations, real good, real bad, not good, or not bad prove significant and so, they were ignored for the rest of the tests. Upon finding evidence for the Twitter factors being related to stock price, I formulated an ARIMA model including the S&P 500 index price to see which factors could act as accurate forecasters.

ARIMA Models

I wanted to account for the S&P 500 price in this analysis as an independent variable. The reason is that the S&P 500 is correlated to individual stocks; the three stocks average correlation with the S&P was .776. To test my hypothesis, I did not want the trend of the S&P to affect the forecast. I wanted to uncover whether people's feelings toward companies affected stock price and so, I needed to compare the Twitter data to the stock movement that the S&P 500 does not account for.

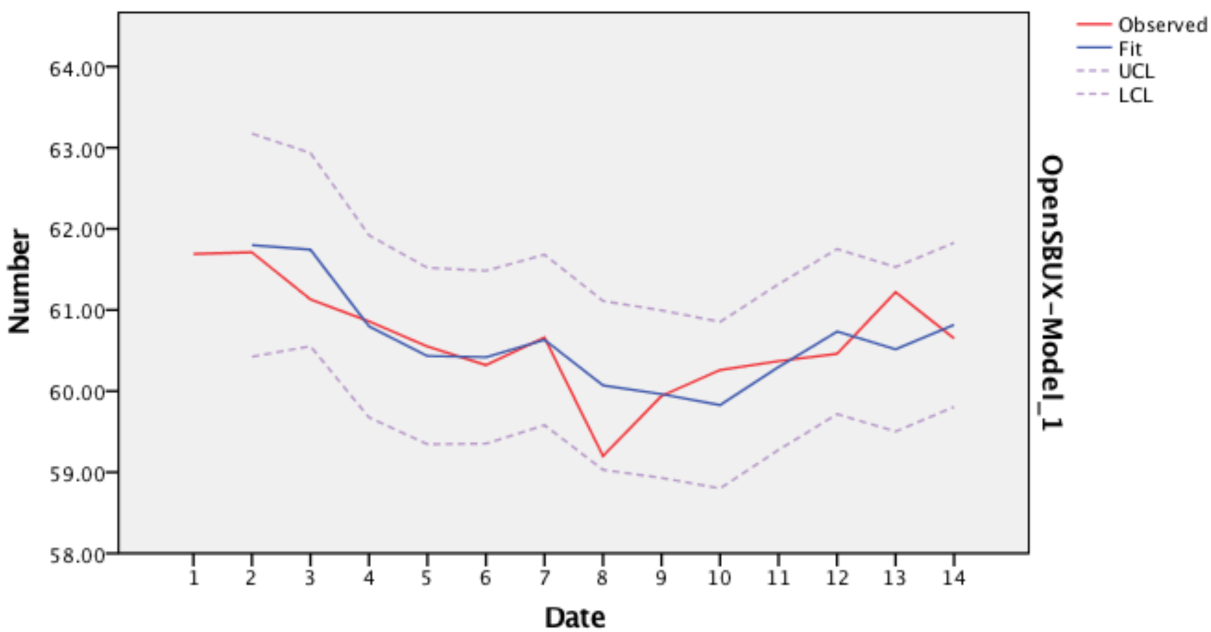
I analyzed each company's stock and Twitter data based on the relationships found in the cross correlations as well as the corresponding S&P 500 price. The Twitter data and S&P 500 were independent and the open price of the stock was the dependent variable. When accounting for the S&P, many of the previous correlations failed to be accurate forecasters as the index was so strong that it made their correlation insignificant. For each company, only one Twitter factor was found to be significant when in a model with the S&P 500 and the open price. You can see the results of the significant models in Tables 1-3 and Figures 9-11.

Table 1: Starbucks ARIMA Model Results

ARIMA Model Parameters

					Estimate	SE	t	Sig.
OpenSBUX-Model_1	OpenSBUX	No Transformation	Constant		-13.430	21.707	-.619	.551
			Difference		1			
			MA	Lag 1	.965	3.175	.304	.768
	OpenSP	No Transformation	Numerator	Lag 0	.008	.010	.730	.484
	TOTWORDSSBUX	No Transformation	Numerator	Lag 0	-.112	.045	-2.522	.033

Figure 9: Starbucks Observed Open Price vs. Starbucks Model Fit



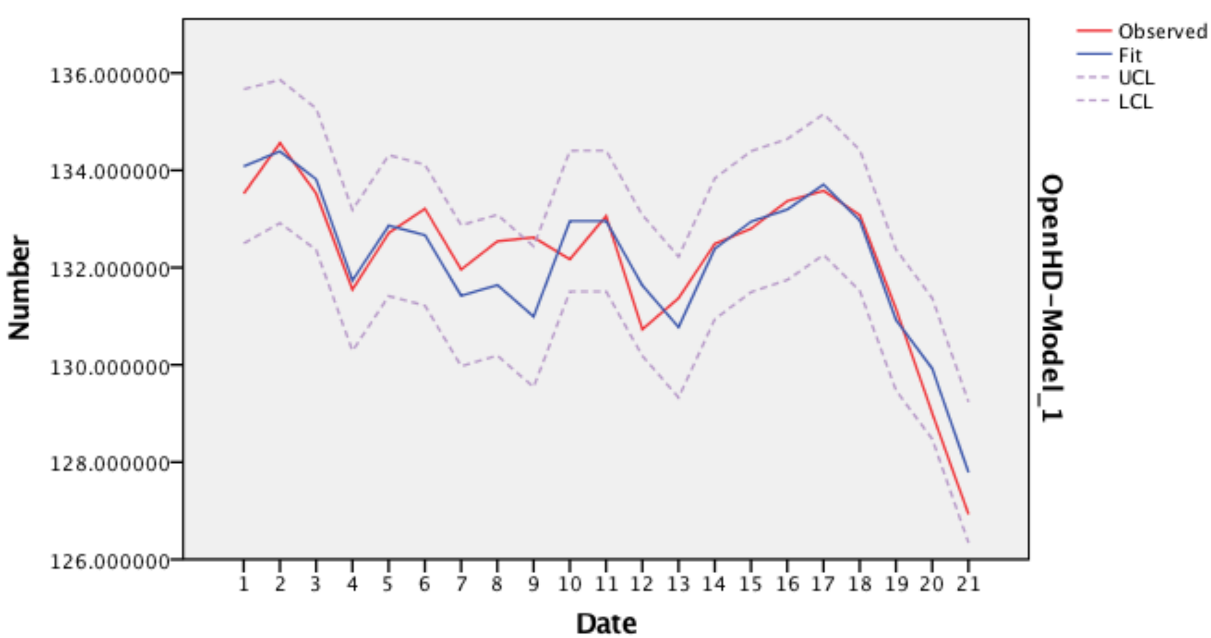
As you can see, the mean of total words for Starbucks tweets is a significant negative predictor of the opening price when controlling for the S&P 500 index with a significance value of 0.033. As you will see in the next two models as well, the ARIMA model parameters had to be adjusted in order to create an accurate forecast. For Starbucks, the parameters of auto-regression, difference, and moving average were adjusted from [0, 0, 0] to [0, 1, 1]. The 0 means that the stock price of Starbucks yesterday was not used to predict the stock price today. The second 1 means that the model is forecasting based on the difference between open prices on each date, as opposed to the open price itself to make the data more linear and easier to predict. The third 1 means that the model is using the moving average of the data lagged one day to better forecast the open price. You can see how the model forecasted versus the observed values in Figure 9. For Home Depot, the model differed a bit.

Table 2: Home Depot ARIMA Model Results

ARIMA Model Parameters

					Estimate	SE	t	Sig.
OpenHD-Model_1	OpenHD	No Transformation	Constant		31.401	13.870	2.264	.037
			MA	Lag 1	-.444	.224	-1.983	.064
	OpenSP	No Transformation	Numerator	Lag 0	.050	.007	7.477	.000
	TOTSUMHD	No Transformation	Numerator	Lag 0	-8.308E-5	3.415E-5	-2.433	.026

Figure 10: Home Depot Observed Open Price vs. Home Depot Model Fit



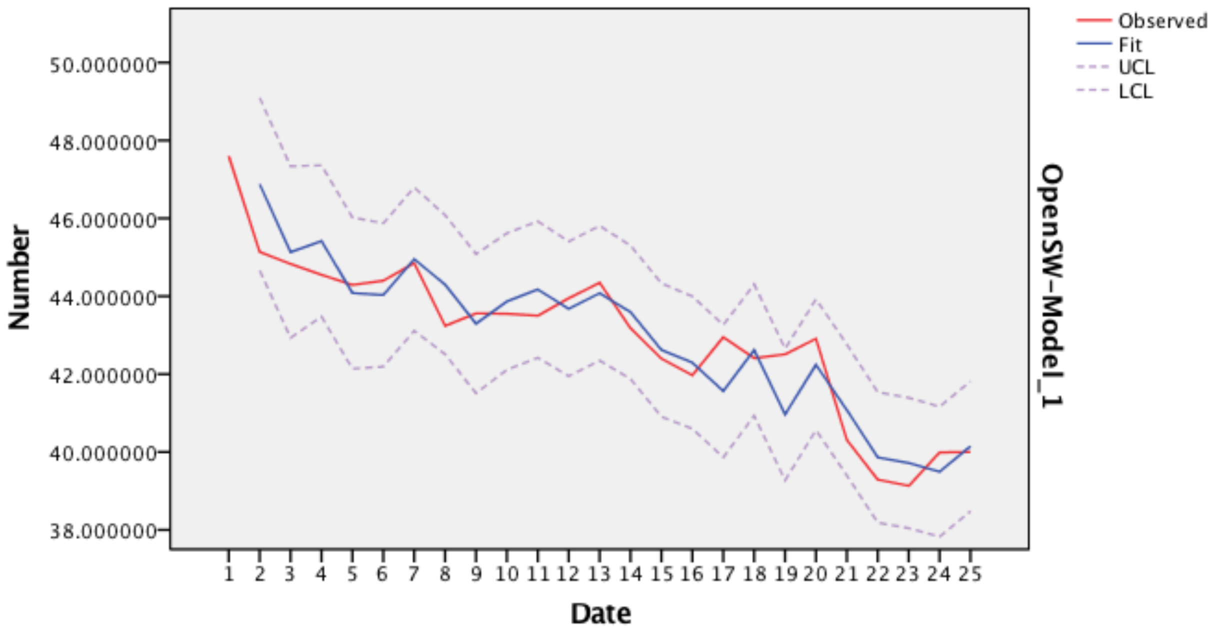
In this case, the sum of total words of the Tweets is a significant negative predictor of the opening price when controlling for the S&P, with a significance value of 0.026. The ARIMA model parameters were adjusted to [0, 0, 1]. This means that the model is taking into account the moving average for each successive time period with a lag of one. It does not use the price of the day before to predict today and does not use the difference between prices either. You can see the forecasted prices versus the observed prices in Figure 10. Again, the Southwest model is a little different.

Table 3: Southwest ARIMA Model Results

ARIMA Model Parameters

					Estimate	SE	t	Sig.
OpenSW-Model_1	OpenSW	No Transformation	Constant		2.980	3.483	.856	.404
			AR	Lag 1	-.246	.363	-.678	.507
				Lag 2	.044	.420	.106	.917
			Difference		1			
			MA	Lag 1	.014	168.513	8.303E-5	1.000
				Lag 2	.986	165.994	.006	.995
	OpenSP	No Transformation	Numerator	Lag 0	-.002	.002	-1.145	.268
	NEGSUMSW	No Transformation	Numerator	Lag 0	.001	.001	2.805	.012

Figure 11: Southwest Observed Open Price vs. Southwest Model Fit



This model had an even higher significance value of 0.012. The sum of negative words in Tweets about Southwest are a significant positive predictor of the opening price of Southwest, controlling for the S&P 500 index. The model parameters here had to be adjusted to [2, 1, 2]. As stated, in a time series often the best predictor of the dependent variable is itself. So, the model is using data from the stock price 2 days ago to predict it today. The following 1, like Starbucks, tells us that the model is also using the difference between stock price today and stock price yesterday to make the data more linear and easily forecasted. Finally, the last 1 tells us that the moving average lagged by one day is also used to predict the stock price. You can see how the model forecasts versus the observed values in Figure 11.

Chapter 4: Discussion & Conclusion

Interpretation

When interpreting the results from these three companies, I have found it important to keep the analysis separate between them. Each company had a slightly different Twitter factor that was a significant forecaster and each model had slightly different parameters. This means that I cannot say there is an overarching model for Twitter to predict individual companies. My research cannot say why this is. These companies are all in different industries and offering different products. It's possible that people interact differently on Twitter with different product offerings, meaning that public sentiment will translate differently into stock price. What I can say is that with a customized model for each, Twitter data can be used to predict stock price, affirming my hypothesis.

For Starbucks the data is indicating that the more words people use in their Tweets about the company, the stock price will decrease in the following day. To clarify, this is not number of Tweets, but the average words per Tweet. My data cannot prove why this is the case, but I can attempt to interpret this in a few ways. It's possible that when people feel negatively about Starbucks, they will rant and say a lot about it. When they feel positive about Starbucks, their feeling is communicated short and simply. It's also possible that more bearish investors tend to say more in their Tweets, while more bullish investors tend to say less.

For Home Depot, the data is telling us that the more words Tweeted about a company, the lower the stock price will be the following day. Again, my research cannot be certain about why this may be the case, but one can speculate. It could be because when people feel negatively about Home Depot they Tweet a lot and say a lot about it. When they feel positively, they may not Tweet about it. Individuals on Twitter may think more of Home Depot when they are feeling negatively about it as opposed to positive. They aren't even necessarily saying anything negative in their Tweets. This reminds me of how it's often said that the news is primarily negative news, but this is because normally things happen in an expected and good fashion. So, when something bad happens it is unexpected and therefore worth putting on the news. This could translate to Twitter as when something negative happens, people want to Tweet about it, but when good or expected things happen then there isn't as much to say.

For Southwest Airlines, there is an interesting observation. The more negative words Tweeted in a day with relation to Southwest, the more positive stock price would be the next day. This seems counterintuitive, but maybe it isn't. The first parameter of auto-regression has a value of 2. This means that the stock price two days ago is a better predictor of stock price today than the stock price yesterday. This indicates to me that people overreact when buying and selling Southwest. Potentially, they may buy or sell too much on one day based on recent news, and then the next day stock price will even back to closer what it was two days ago. So, potentially on day one some news comes out about Southwest or the industry in general. The next day, people are saying overly negative or positive things about the company and stock price reacts that day accordingly. Then, the next day the market realizes it has overreacted and corrects itself a bit. Again, my analysis cannot say why the relationships are the way they are, but I am simply trying to make an educated conclusion based on the model results.

Implications

Regardless of why these predictive relationships between Twitter and stock price exist, it is valuable to know that they do. In the case of an investor, this can help for certain horizons. Long-term, I don't believe my research will contribute much value. I don't believe the Twitter analysis I did will correlate to long-term performance, which is more based on the actual profitability of a company. In the short-term, I think this research can be valuable to investors. I would not recommend using these ARIMA models as the only decision for making a short-term investment, but they certainly can fit into a larger model. If an investor gets an indication that stock is going up or down the next day from this Twitter data, assuming they have access to it, they can make more informed decisions and potentially make a large profit. In the case of institutional investors, my research has shown that incorporating Twitter data even for individual companies can give an indication to stock movement and be an area to attain profit. For companies, this research could also be valuable. The Twitter factors that forecast stock price, such as total words or negative words, gives a signal to how individuals interact with their brand. For example, if the company determines that the more people say about the company on Twitter translates to a lower stock price then they may want to change how they interact with customers on social media to try to get more positive sentiment. It also may be helpful to know where your stock price is going the next day.

Limitations

There are some limiting factors in this research that I would like to address. For one, although I provided my interpretation of this research, my data does not and cannot give any indication as to if this interpretation is true. It may be dangerous for someone investing real money to trust these models without knowing the why behind it. Another limitation is that it is unknown why each company required a different model to forecast it. Is it because there are different product offerings? It's possible that over a longer time period, the same stock may need a different model, which would limit the use of the research. On the same note, my research covers a relatively small amount of time. The longest dataset covers just over a month. This was due to resource constraints, but it would have been more useful to look at the stock over the course of a year or more to ensure that the forecast holds true for a longer period of time. Another limiting factor is the lack of stock data over the weekend. Due to this, we could not use two days of Twitter data. Although we tested different five days of the week, it is still possible that the two ignored days contained data that could have been useful to the analysis.

Opportunities for Future Research

There are two main avenues for future research. One would be to determine if this research applies to other companies as well. The interesting thing to see would be if other stock prices could be forecasted using Twitter data in ARIMA models and what kinds of companies were forecasted using the same Twitter factors and ARIMA parameters. If companies had the same kind of product, is their stock price predicted by the same

Twitter factors? This information could help give more insight into why the models work the way they do. The other main avenue for future research is why the particular Twitter factors forecast stock price. Why do total words or negative words show a relationship with stock price? Answering these two questions would give enormous insight into how exactly the relationship between what people say on Twitter and stock performance works. I believe that would help guide short-term investing decisions. After learning these things, it would be interesting to see how a portfolio performed based on the forecasts of this model.

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